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Research Article

Deep Learning Model for Hand Movement Rehabilitation

Reem D. Ismail [1], Qabas A. Hameed [1], Mustafa Abdulfattah Habeeb [1], Yahya Layth Khaleel [1], Fatimah N. Ameen [2,*]

[1] *Department of Computer Science, Computer Science and Mathematics College, Tikrit University, Tikrit 34001, Iraq*

[2] *Institute of Automation and Info-Communication, Faculty of Mechanical Engineering and Informatics, University of Miskolc, Miskolc, Hungary*

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ABSTRACT

Electroencephalography (EEG) can control machines for human purposes, especially for disabled people doing rehabilitation exercises or regular tasks. Brain-computer interface (BCI) for Robotic hand uses deep learning to convert (EEG) brain activity into orders for robotic hand allowing users to move their hands right or left by the movement imagining. It could enable paralyzed individuals to perform basic hand movements and help in rehabilitation robots that help stroke patients regain hand function by offering guided exercises based on machine learning interpretations of their movements and intents. Artificial intelligence algorithms, particularly deep learning, classify and recognize patterns and intents implicit brainwaves as electroencephalography. However, EEG signals have a high degree of no stationarity, making their analysis challenging. As a result, selecting a suitable signal-processing strategy becomes critical. This study aimed to build a hybrid model to direct robotic arm movement, which applied movement direction and right or left classification. By integrating a pre-trained convolutional neural network (CNN) - the Inception V3 Model with a traditional machine learning algorithm (logistic regression (LR)), which is considered an extensive classification method, as well as identify a suitable signal processing method, the short-time Fourier transform (STFT) and continuous wavelet transform (CWT) to select the most accurate method for proposed model's classification. The training results of the proposed hybrid model show that STFT achieves higher average accuracy (0.998) than CWT (0.997), making it more precise for classifying the current dataset of nine subjects and enhancing the effectiveness of hybrid CNN model training. Similarly, the evaluation result of the average accuracy achieved by STFT is higher than that achieved by CWT in the evaluation metrics (0.997 > 0.797). This suggests that STFT is a superior choice for feature extraction, improving the generalization and robustness of the hybrid CNN model with logistic regression.

1. INTRODUCTION

The human brain has been investigated for decades because of its captivating nature as a dynamic and complex structure [1]. First, in 1924, Hans Berger, a German psychiatrist, successfully recorded the electrical activity of the cerebral cortex using EEG, demonstrating that it is possible to see how the brain operates [2]. The electroencephalogram (EEG) measures neuronal activity in the form of electric currents generated by a set of specialized pyramidal cells within the brain [3]. EEG is a more potent tool for brain imaging activities than other functional neuroimaging techniques because of its low cost, high flexibility, high temporal resolution, non-invasiveness, ease of use, portability, and safety [4], such as positron emission tomography (PET), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), and transcranial magnetic stimulation (TMS) [2][5]. EEG signals can detect depression, epilepsy, and weariness. However, it also has certain snags, such as the difficulty in collecting data and the fact that the data obtained is typically too noisy [6]. EEG and motor imagery (MI) signals have recently received a lot of interest since they indicate a person's intention to execute an activity. Researchers have used MI signals to help persons with disabilities use wheelchairs and other devices [7, 8]. MI pattern recognition systems involve three primary steps: pre-processing the EEG signal, feature extraction, and classification. Feature extraction is critical in the MI-EEG pattern recognition model [4][9]. The uniqueness of each

*Corresponding author. Email: ameen.fatima.nadhim@student.uni-miskolc.hu

individual's EEG waves hampers the universality of BCI design. On the contrary, this is thought to be useful for employing EEG signals from imagined activity in biometric applications. BCI systems are used in various applications, including communication, neuroprosthetics, and environmental control. These technologies are especially useful for persons with disabilities, allowing them to engage with robots and manipulators [10, 11].
On the other hand, AI is the branch of computer science that deals with achievement of methods and models that are said to possess the abilities that human beings have in their intellectual prowess [12]. In artificial intelligence, Machine learning is one that utilizes algorithms to make predictions or decisions based on data [13, 14] whereas deep learning is a subset of machine learning that utilizes neural networks with multiple layers that makes it efficient in areas involving pattern analysis such as image or speech recognition [8][15, 16]. Combined, they allow the formulation of complex systems that have the ability to process, learn and execute a number of applications apart from collecting and processing big data. Moreover, brain-computer interface systems have evolved to explore new ways to use their potential to improve people's lives. Brain-computer interface systems primarily seek to build a direct communication link between the brain and an external device, bypassing the body's more common pathways of nerves and muscles. In which users visualize doing a specific action without actually completing it, has emerged as a potential strategy for improving communication and control in individuals with motor disabilities and general-purpose applications [17, 18]. Current BCI trends are focused on neuroprosthetic applications such as repairing impaired hearing, sight, and movement. Similarly, prostheses can replace defective nervous system functions, brain-related issues, and sensory organs. Furthermore, BCI systems could be employed for more advanced non-medical applications such as gaming and smart home control [11][19]. These systems could use for emotion recognition has the potential to enrich human-computer interaction with implicit information since it allows for a comprehension of human cognitive and emotional activity [20, 21].
The time frequency representation of motor imagery features is commonly employed in BCI applications especially for the purpose of classification. This approach depicts the concentration and activity of signal energy from different time periods and scales as a time-frequency function [22, 23]. As previously mentioned, MI signals are largely one-dimensional and need to be transformed to two dimensions and this is well done using the CWT and STFT. Both being efficient methods the above approaches are useful in controlling signal characteristics in the time as well as the frequency domains [24]. EEGs are typically considered as non-stationary signals when records are analyzed over the short time period and this makes their analysis cumbersome [25]. Convolutional neural networks are also able to obtain the spatial and temporal features of MI datasets through shallow and deep layers for extracting basic and important features at different levels of CNN architecture [26, 27]. Further improvement of BCI systems happens with deep transfer learning as new data could be incorporated into already trained models, which is useful when new data can hardly be effectively trained due to its rarity [28, 29]. It shows that subject-transfer techniques that utilise CNNs deliver better results than the other methods, thanks to the similarities in patterns, which the intended subject and others with similar functions share [30], [31]. Nonetheless, in the existing research on hybrid models, emphasis is accorded primarily to the application of different classifiers, as well as deep learning CNN models without a comprehensive analysis of the STFT and CWT techniques on different datasets to identify which of the methods is most beneficial for the proposed model [4][7][32].
On the other hand, brain commands can be utilized to control several sorts of robots. Brain-robot interface systems have seen an increase in applications ranging from rehabilitating people suffering from mental traumas such as cerebral stroke to identifying psychological and neural illnesses, as well as component assembly. This revolutionary mode of engagement has opened up a new realm of applications. BCIs using non-invasive electrodes have been employed to control robotic hands, as well as autonomous navigation robots, drones, and wheelchairs [33, 34]. Figure 1 showed Statistical Classification of BCI-Controlled Robotic Devices bases Applications.

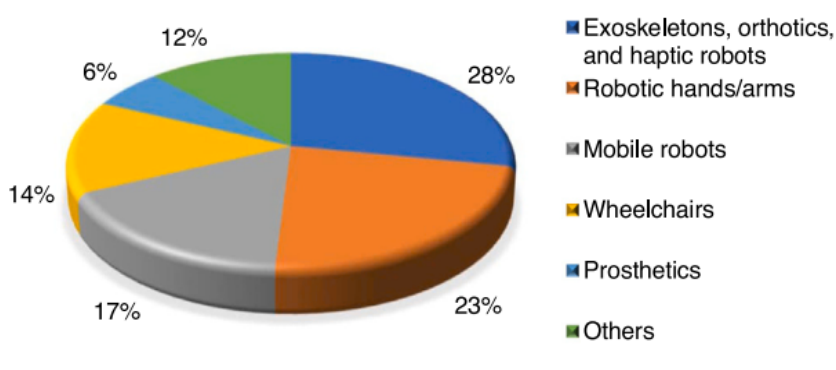

Fig. 1. Statistical Classification of BCI-Controlled Robotic Devices Across Applications [33]

Brain-computer interface (BCI) for robotic hand uses deep learning to convert (EEG) brain activity into orders for robotic hand, allowing users to move their hands right or left by the movement imagining. It could enable paralyzed individuals to perform basic hand movements and help in rehabilitation robots that help stroke patients regain hand function by offering guided exercises based on machine learning interpretations of their movements and intents. Rehabilitation robots use Deep learning to help people regain control of their hand movements [35-37]. This paper aims to build a hybrid model to classify the right or left-hand movement precisely based on EEG signals and utilizing motor imagery, besides identifying suitable signal processing method among famous approaches, namely short-time Fourier transform (STFT) and continuous wavelet transforms (CWT) and choose the most accurate transform for proposed model's classification. This model will control tasks (the right and left movement). This paper is organized as follows: Section 2 background and significance, Section 3 outlines the study's methodology. Section 4 presents the Results and Discussion. Finally, Section 5 and 6 presents the future work, and conclusions of the study.

2. BACKGROUND AND SIGNIFICANCE

Motor imagery based BCI or MI-BCI has attracted increased interest in the field of rehabilitation and assistive technologies [38, 39]. During motor imagery the active zones in the cerebral cortex involved are the supplementary motor area (SMA) and parietal cortex which consists of the superior and superior parietal lobules [40]. In addition, mirror neuron system (MNS) is one of the most important factors in motor imitation and comprehension of others intention which is very relevant to motor imagery [41, 42]. It has been established that motor imagery facilitates motor learning through mental practice and rehearsal of movements thus enhancing the cognitive structuring of actions [43]. This enhances activations in neural circuits that are similar to the circuits that are activated during the actual plan implementation leading to neuroplastic changes in support of motor learning [44]. Furthermore, the use of motor imagery has been shown to have substantial novelty in different disability conditions such as the rehabilitation of stroke, spinal brain, traumatic mind, and immobilization paralysis conditions, Parkinson’s ailment and cerebral palsy as well as musculoskeletal diseases [45].
Research has highlighted the effectiveness of using virtual reality (VR) in the training strategies on rehabilitation and more specifically for the stroke patients with severe motor impairment [46]. Oddly, through VR technology it is possible to build a physical environment within a virtual reality where one can perform interaction supported by the physical ability of movements leaving aside the severe physical impairments, thus improving the communication and possibility of purposefully trained patients [47]. Research has further shown that motor imagery can facilitate the activation of those areas of the brain and that the integration of the VR and the MI-BCI can help reform the central nervous system among the motor-disabled patients [48, 49]. Furthermore, owing to the nature of VR technology the patients can mimic actual movements much more effectively and generate clear EEG patterns [50]. The use of VR and MI-BCI as a concept shows potential in improving the overall results of rehabilitation and improving the experience of persons with disabilities [36]. It is necessary to do more empirical studies in this area so as to build more flexible and realistic VR scenes for rehabilitation training to enhance the stimulation of motor imagery [22].

2.1 Rehabilitation and assistive technologies

Several authors researches that the use of rehabilitation and assistive technologies has a significant impact in enhancing the quality of life of the persons having motor disabilities [36]. Recent experiments involving using motor imagery based BCI for the rehabilitation of patients or improvement of assistive technologies have been indicating the potential of the concept [51]. The motor imagery intervention helped patients with cerebral palsy in the area of upper limb movement, gait, and balance. Moreover, motor imagery has been observed to help in relieving pain intensity, improving joint movement and quickening the rehabilitation process of people with musculoskeletal illnesses [52]. In addition, the inclusion of motor imagery exercise in a rehabilitation program has been revealed to improve motor learning and practice, encourage neuroplasticity process, and enhance functional improvement in stroke, spinal cord injury, traumatic brain injury, Parkinson’s disease, and musculoskeletal disorders [53].
Also, the integration of VR technology and motor imagery brain computer interface (MI-BCI) provided an immersive feature for training as well as facilitated precise measurement of MI thus creating recognisable EEG pattern [54]. Though, this approach has been effective mostly with stroke patients with flaccid paralysis are benefitting from intention training in virtual environment enhancing the rehabilitation training effects [55].

2.2 Motor imagery-based brain-computer interface systems

Studies have shown that, through motor imagery based BCI systems, motor function can be enhanced in people with arthritis and multiple sclerosis, amongst other diseases [56]. The rehabilitation of the nervous systems of patients and the improvement of the quality of life in patients with motor disorders are made possible by these systems [57]. For instance in stroke rehabilitation, motor imagery has been found useful in promoting the rehabilitation of upper limb functions by a process of mental practice [58]. This helps stimulate neural pathways and facilitation occurs for the brain to re-map and have motor control. Since motor imagery-based BCI systems feedback in real-time, patients are able to see the intended movements and participate in their rehabilitation [59]. Likewise, the implementation of these systems is helpful for people who have spinal cord injuries since mental practice helps to enhance their motor function and quality of life [60]. Another application to TBI patients is motor imagery exercise which can activate a impaired neural networks and enhance neuron plasticity on motor control and cognitive processes [61]. It has been testified that Parkinson's disease patients could benefit from motor imagery in terms of motor deficits, bradykinesia, balance, and gait. In addition, these systems have been discussed in relation to cerebral palsy, as well as to arthritis, and multiple sclerosis and the findings have also showed enhanced physical status in addition to the quality of life in patients [62]. Altogether, motor imagery-based BCI systems possess a huge potential in the field of rehabilitation and assistive technologies with constant further investigation on exploring the full potential of the systems in the context of the neurorehabilitation advancement [56].

3. METHODOLOGY

The methodology of the proposed hybrid model for classifying the right or left-hand movement based on EEG signals and utilizing motor imagery is produced in Figure 2. The details of the concept and implementation of this model are explained in the following subsections.

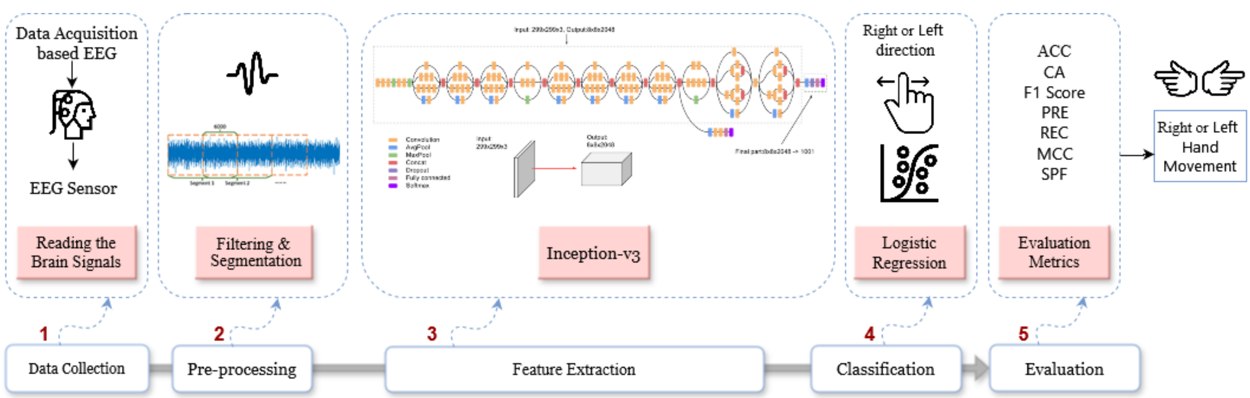

Fig. 2. Methodology of the Proposed Hybrid Model

3.1 Datasets collection

The strategy adopted by the brain-computer (BCI) systems developers usually chooses to use a few channels, facilitating the deployment and application of real-time applications at decreased costs [63]. Consequently, this study selected two MI EEG datasets that were recorded utilizing three channels. The two datasets used were sourced from the BCI competition datasets, notably those recorded at Graz University. The following subsections provide more information about the two datasets. The datasets consist of two independent parts: training and evaluation. Thus, the hybrid model was employed to examine the variances between the inter- and intra-subject [9]. The datasets of all nine participants needed to be combined to generate a complete dataset involving all experiments and the restricted availability of a substantial dataset. This approach has created a robust model capable of successfully dealing with the intricate issues connected with brain complexity.

In this study, electroencephalogram (EEG) signals were recorded using three specific channels: of C3, Cz and C4 electrodes. These channels were chosen to record the brain electric activity related to two different motor imagery tasks, that involved visualization of movement of left and the right hand. The dataset was acquired from nine subjects; the signals were sampled at 250Hz. In total, 160 experiments were performed to obtain complete EEG information about each participant; the person was comfortably seated in an armchair with a flat-screen in front of him. The data collection process was structured into two separate phases: The main crew activities include the training sessions, and the evaluation sessions. In the case of training, participants had no information concerning correct responses, while, in the case of evaluation, participants were informed about the correct responses to the training stimuli. The first two sessions were composed of the exposure of the participants to a brief auditory stimulus, a warning tone, which indicated that they were to start an intercalar four seconds motor imagery task. In this exercise, the subjects' task was to imagine a particular movement when they heard an auditory stimulus in the form of a pointing arrow on the otherwise black screen. After the first few meetings, three further meetings were held, at which more precise instructions were given. This time they were expected to control a grey smiley face which was placed at the centre of the screen and shift it to the left or right depending on yet another auditory signal. The feedback was intended to be immediate, by four seconds a smiling face was loaded on the screen that lit green if the participant shifted the face in the correct direction as required, otherwise it turned red. This feedback mechanism was supposed to give the participants a live validation of their motor imagery performance, which would have promoted the learning and the adaptation processes [22][64].

3.2 Pre-Processing

MI-related EEG signals are subjected to a variety of noise that consequently affect the interpretation of the results. These are body motions, eye lid twitches, facial muscles contractions and other outside interference like electromagnetic interference from the other electrical appliances [65]. They can significantly affect the quality of signals produced by the equipment and accumulated in the baseline, in the course of EEG-MI, so that the specialists face a difficult task in analyzing and interpreting the brain activity. In order to tackle this problem, the study used deep learning strategies It was established that these approaches demanded marginal preprocessing in that they could learn features from p-samples directly. The most important of them is frequency filtering whose main function is to improve the signal to noise ratio of the recorded raw EEG data so as to boost the relevant brain signal information. In particular, a fourth-order Butterworth filter was used, that aims at the removal of high-frequency noise within the range of 8-30 Hz. This range was selected to accommodate the crucial aspects of MI EEG data the chief of which resides in the alpha (8-13 Hz) and beta (14-30 Hz) bands. These bands are tightly linked with the motor imagery processes and filtering within this frequency restricts noise while helps in maintaining the relevant EEG oscillations, hence used for our analysis.

3.2.1 STFT for EEG Image Formulation

STFT is developed by Gabor in 1946, is a widely used signal processing algorithm for analyzing non-linear and non-stationary signals. It provides the phase and magnitude of a signal, detailing its frequency components over time [66]. It divides a long signal into segments of equal window size and applies the Fourier transform to each [67]. STFT is an advanced Fourier analysis in which a signal is presented in a way that allows for comprehensive estimation in both domains. It uses a window function to extract a piece of the time domain signal and then applies the Fourier transform to determine various signal aspects [19][68]. For STFT, the processed EEG signal x(t) is multiplied by a short time window that slides along the time axis, resulting in a set of windowed signal segments. Lastly, the Fourier transform is applied to each windowed signal segment, resulting in two-dimensional time-frequency spectrums for the raw signal. STFT can be defined mathematically [4][67, 68] as in equation (1):

$$STFT\ (\tau,\omega) = \int_{-\infty}^{+\infty} dt\ w(t-\tau)\ e^{-i\omega t} dt\ \ldots\ (1)$$

The efficiency of the STFT for creating 2D images (spectrograms) of 4 s length and feeding them to the CNN as input images is reported in [69]. For this reason, a length of four seconds was chosen, yielding a total of one thousand samples for each MI signal in the Xi trial. After that, we selected a window size of 64 samples with 50-sample overlap to generate images depicting the power spectral density (PSD) of motor imagery (MI) signals, with values measured in Hertz. So, three images are yielded per set of data collected from three electrodes. This study aimed to focus on alpha and beta frequency bands associated with event-related synchronization (ERS) and desynchronization (ERD) motor activity, and six images per MI trial were produced.

3.2.2 Continuous Wavelet Transform (CWT)

CWT is an effective time-frequency representation (TFR) method that produces an overly detailed signal description. It depicts signals as a linear combination of principle or basis functions known as wavelets localized in time or space. It enables the analysis of localized signal content. CWT transform provides the added benefit of visualizing the wavelet coefficients' magnitude, allowing us to notice when and which frequencies are stimulated and their length, time evolution, and density [70], [71]. CWT can be defined mathematically as in equation (2):

$$CWT\ (2\pi f, s) = 1 / |s|^{1/2} \int x(t)\, \psi(t - 2\pi f / s) dt \ldots (2)$$

In Equation (2), $x(t)$ represents a time-series signal, ψ is a pre-defined mother wavelet, t is the time-shifting parameter, i.e., translation parameter, and s is the scaling parameter [32]. Mainly, continuous wavelet transforms (CWT) and short-time Fourier transforms (STFT) are often used to convert MI signal is one-dimensional to a two-dimensional image. These highly successful approaches can process signal properties in both the temporal and frequency domains [4][68][71]. In the current proposed model, the utility of time-frequency representation (TFR) method is examined on a hybrid model for the classification of the right-hand movement (RHM) and left-hand movement (LHM) MI tasks based on EEG signals. The considered TFR methods are short-time Fourier transform (STFT) and continuous wavelet transform (CWT).

3.3 Feature Extraction used Inception V3 Model

The classification of EEG signals necessitates high-dimensional features to capture the latent features of the brain activity signals. CNN relies on convolutional processes to extract prominent features using several kernels (filters) [68][72]. A CNN is defined as a technique for classifying data in images, specifically emphasizing image recognition challenges [18], [23]. The CNN model's strength is its hierarchical learning layer, which may be extensively trained, provided the model topology matches the input data. The model efficiently decreases the number of parameters and enhances performance accuracy by utilizing the spatial relationship of visual patterns [18]. CNN with transfer learning, which refers to applying an existing model's weights and layers to a new untrained model, accelerating the learning of the new model [73], [74], aids very accurate identification of different affect states, hence increasing human-computer interaction [29].

Google developed Inception V3, CNN architecture designed primarily for image categorization problems. It is the third generation of the Inception architecture, first released in 2015. Inception V3 Intending to improve the efficiency of performance and image classification tasks, it builds upon its predecessors' concepts. The Inception V3's architecture is complex and sophisticated, with interconnected inception modules. Each module combines convolutional and pooling layers to extract distinct features from the input image. Inception V3 is notable for its use of factorized convolutions, which reduces the number of parameters in the network while maintaining excellent accuracy. Factorized convolution enhances model accuracy by enabling the network to learn an image's local and global features. It combines 1x1, 3x3, and 5x5 filters, where 1x1 filters reduce the input's dimensionality, and 3x3 and 5x5 filters extract more complex features from the image [75-78]. Inception-V3 architectural model has an advantage because of its more intricate architecture and more efficient computation; it contains approximately 4 million parameters, is significantly smaller than VGG, has a more complex architecture, and does not use a fully connected layer but relies solely on a pooling layer. These fewer parameters result in a reduced model size, which allows for faster model calculations. Inception V3 also uses batch normalization, another notable characteristic for standardizing network inputs. Batch normalization helps to stabilize the training process and reduces the internal covariate shift, which is the change in the distribution of the network's inputs during training. Also, it is frequently used for image classification applications and has demonstrated significant performance on various benchmarks. It has been employed in various applications, including object identification, picture segmentation, and video categorization [76-79]. Figure 3 describes the structural schematic diagram of the Inception-v3 model.

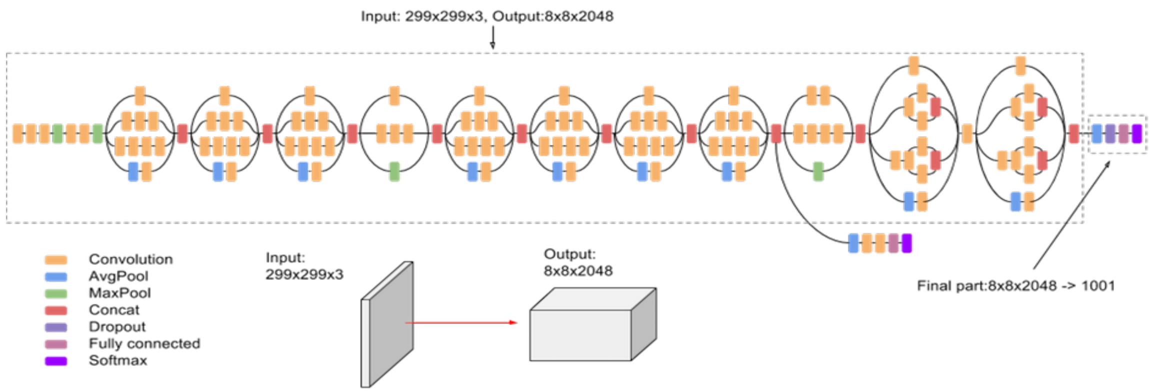

Fig. 3. The Structural Schematic Diagram of The Inception-V3 Model [80]

3.4 Classification Used Logistic Regression (LR)

The classification technique was effective in discriminating between two MI EEG mental orders. This study aimed to build a hybrid model to direct robotic arm movement by hybridizing a pre-trained CNN with a traditional machine-learning algorithm [7][81].

Logistic Regression (LR) is a statistical technique using a decision boundary to classify observed data into two categories (pass or fail). This alternate data classification method is appropriate for both tasks (multi-class and binary-class). LR is a widely used generalized linear model in machine learning and other medical fields. It calculates the likelihood of a binary result by combining one or more predictor factors and using a logistic function. Two essential parameters (penalty and C) must be adjusted to set the mathematical norm for penalization; the penalty parameter is used. As well as, the inverse of C represents the regularization strength, with smaller values indicating more robust regularization [82-84].

The classification process uses the evaluation criteria which will present in next section, to demonstrate and determine the suggested model's robustness, efficacy, and generalizability.

3.5 Performance Evaluation

A performance evaluation metric is useful to determine how well a model performs against a particular dataset in machine or deep learning. It assesses how effectively a trained model addresses the problem for which it was offered [85]. The performance of the proposed hybrid model will be analyzed and evaluated using standard metrics pre-used in the literature.

3.5.1 Evaluation metrics:

Evaluation metrics are an important part of the ML workflow because they allow to quantify the effectiveness of our proposed models and make data-driven decisions about how to improve them when compared to other existing ML techniques [86].

In machine learning, many evaluation metrics are available that can be used depending on the model's purpose and objectives. For example, metrics are used for classification tasks to evaluate the model’s performance such as accuracy, F1 score, Precision, Recall, MCC, and specificity. These metrics help to compare different models and choose the best-performing model based on validation or test data. They can also be used to identify regions of the model that require improvement and to direct efforts to alter the model's hyper-parameters or features. Table 1 shows the details of performance evaluation metrics [86,87].

TABLE I. THE DETAILS OF PERFORMANCE EVALUATION METRICS FOR MODEL CLASSIFICATION

Metric	Abbreviation	Definition	Formula
Accuracy	ACC	Accuracy measures the model's exactness and quality in percentage terms, the ratio of correctness and the total data.	$Acc = \frac{TP + TN}{TP + TN + FP + FN}$
F1 Score	F1 Score	The F1 score evaluates the correctness of the detection.	$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recal}$
Precision	PRE	The precision determines the classification strength of a particular model.	$Pre = \frac{TP}{TP + FP}$
Recall	REC	The recall score retains the analysis, indicating proficient detection.	$Recall = \frac{TP}{TP + FN}$
Matthew Correlation Coefficient	MCC	Calculates the correlation between the observed and predicted values.	$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$
Specificity	SPF	The model's efficiency is assessed by its specificity.	$Spe = \frac{TN}{FP + TN}$

4. RESULTS AND DISCUSSION

This section discusses the result of implementing the hybrid model for classifying the right or left-hand movement precisely based on EEG signals and utilizing motor imagery, examining the short-time Fourier transform (STFT) and continuous wavelet transform (CWT) methods on the hybrid model. This model could help individuals perform basic hand movements (the Robotic hand) and help in Rehabilitation Robots that help stroke patients regain hand function. This model will be implemented for the direction assignment via biometric (EEG-signal/ MI) on (nine subjects) dataset to classify the right or left movement. The classification accuracy of the hybrid model that combines pre-trained CNN (Inception V3 embedder) with a LR algorithm for each subject in the dataset has been examined on both the short-time Fourier transform (STFT), continuous wavelet transforms (CWT) for the proposed model.

The average accuracy for the nine subjects was calculated for each of the provided signal processing methods in two parts (Training and Evaluation).

Specifically, in the training part, the performance metrics of the proposed hybrid model were applied using the (CWT) method on the current dataset (nine subjects), with a classification accuracy of 0.997, CA of 0.988, F1 score of 0.988, precision of 0.988, recall of 0.988, MCC of 0.976, and specificity of 0.988, as shown in Table 2.

TABLE II. THE PERFORMANCE METRICS OF TRAINING PART OVER (NINE SUBJECT) DATASET USING *CWT* METHOD

Classifier	Subjects	Performance Metrics						
		AUC	***CA***	***F1***	***Precision***	***Recall***	***MCC***	***Specificity***
Logistic Regression	Su1	0.998	0.980	0.980	0.980	0.980	0.960	0.980
	Su2	0.999	0.991	0.991	0.991	0.991	0.981	0.991
	Su3	0.999	0.994	0.994	0.994	0.994	0.988	0.994
	Su4	0.999	0.980	0.980	0.980	0.980	0.960	0.980
	Su5	0.994	0.995	0.995	0.995	0.995	0.990	0.995
	Su6	0.997	0.980	0.980	0.980	0.980	0.960	0.980
	Su7	0.999	0.992	0.992	0.992	0.992	0.988	0.992
	Su8	0.994	0.989	0.989	0.989	0.989	0.977	0.989
	Su9	0.999	0.991	0.991	0.991	0.991	0.981	0.991
	Mean	0.997	0.988	0.988	0.988	0.988	0.976	0.988

While for the latter using (STFT) method the classification accuracy is 0.998, with corresponding values of CA= 0.992, F1=0.992, Precision=0.992, Recall=0.992, MCC= 0.984, Specificity= 0.992, as shown in Table 3.

TABLE III: THE PERFORMANCE METRICS OF TRAINING PART OVER (NINE SUBJECT) DATASET USING *STFT* METHOD

Classifier	Subjects	Performance Metrics						
		AUC	*CA*	*F1*	*Precision*	*Recall*	*MCC*	*Specificity*
Logistic Regression	Su1	1.000	0.996	0.996	0.996	0.996	0.992	0.996
	Su2	1.000	0.989	0.989	0.989	0.989	0.977	0.989
	Su3	0.999	0.994	0.994	0.994	0.994	0.988	0.994
	Su4	1.000	0.998	0.998	0.998	0.998	0.996	0.998
	Su5	0.999	0.991	0.991	0.991	0.991	0.981	0.991
	Su6	0.996	0.979	0.979	0.979	0.979	0.958	0.979
	Su7	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Su8	1.000	0.994	0.994	0.994	0.994	0.988	0.994
	Su9	0.994	0.991	0.991	0.991	0.991	0.981	0.991
	Mean	0.998	0.992	0.992	0.992	0.992	0.984	0.992

Figure 4 shows the average accuracy at training part using CWT and STFT on the nine subject datasets.

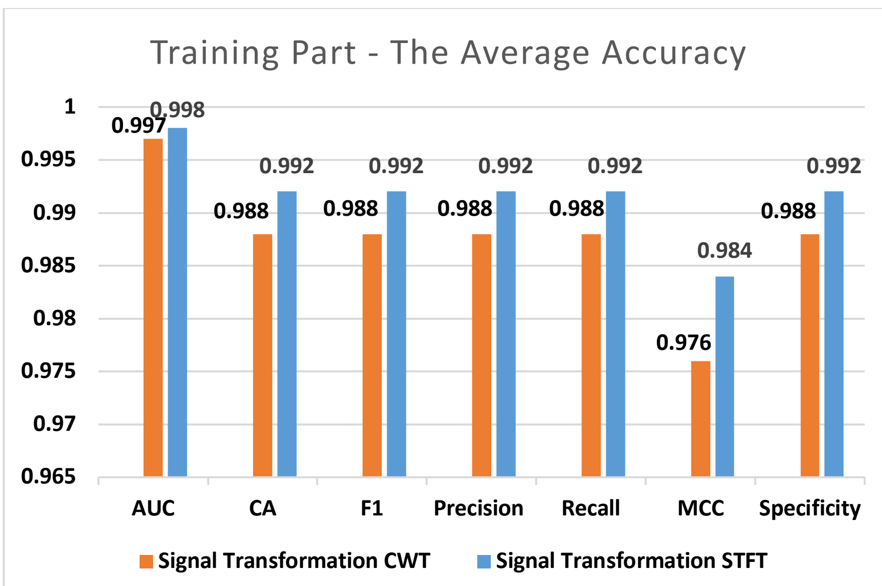

Fig. 4. The Average Accuracy at Training Part using CWT and STFT

Then, in the evaluation part, the performance metrics of the proposed hybrid model were applied using the (CWT) method on the current dataset (nine subjects), with a classification accuracy of 0.797, CA of 0.987, F1 score of 0.987, precision of 0.987, recall of 0.987, MCC of 0.974, and specificity of 0.987, as shown in Table 4.

TABLE IV. THE PERFORMANCE METRICS OF EVALUATION PART OVER (NINE SUBJECT) DATASET USING *CWT* METHOD

Classifier	Subjects	Performance Metrics						
		AUC	***CA***	***F1***	***Precision***	***Recall***	***MCC***	***Specificity***
Logistic Regression	Su1	0.996	0.988	0.987	0.988	0.988	0.975	0.988
	Su2	0.999	0.994	0.994	0.994	0.994	0.988	0.994
	Su3	0.997	0.988	0.987	0.988	0.988	0.975	0.988
	Su4	0.993	0.985	0.985	0.985	0.985	0.971	0.985
	Su5	0.992	0.969	0.969	0.969	0.969	0.939	0.969
	Su6	0.1000	0.994	0.994	0.994	0.994	0.988	0.994
	Su7	0.997	0.986	0.986	0.986	0.986	0.973	0.986
	Su8	0.999	0.989	0.989	0.989	0.989	0.977	0.989
	Su9	0.1000	0.992	0.992	0.992	0.992	0.983	0.992
	Mean	0.797	0.987	0.987	0.987	0.987	0.974	0.987

While for the latter using (STFT), the classification accuracy is 0.997, with corresponding values of CA= 0.989, F1=0.989, Precision=0.989, Recall=0.989, MCC= 0.979, Specificity=0.989, as shown in Table 5.

TABLE V. THE PERFORMANCE METRICS OF EVALUATION PART OVER (NINE SUBJECT) DATASET USING *STFT* METHOD

Classifier	Subjects	Performance Metrics						
		AUC	***CA***	***F1***	***Precision***	***Recall***	***MCC***	***Specificity***
Logistic Regression	Su1	0.997	0.983	0.983	0.983	0.983	0.967	0.983
	Su2	0.997	0.984	0.984	0.984	0.984	0.969	0.984
	Su3	0.993	0.986	0.986	0.986	0.986	0.973	0.986
	Su4	1.000	0.990	0.990	0.990	0.990	0.979	0.990
	Su5	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Su6	0.998	0.982	0.982	0.982	0.982	0.965	0.982
	Su7	0.995	0.991	0.991	0.991	0.991	0.981	0.991
	Su8	1.000	0.996	0.996	0.996	0.996	0.992	0.996
	Su9	1.000	0.994	0.994	0.994	0.994	0.988	0.994
	Mean	0.997	0.989	0.989	0.989	0.989	0.979	0.989

Fig. 5 shows the average accuracy at evaluation part using CWT and STFT on the nine subject datasets.

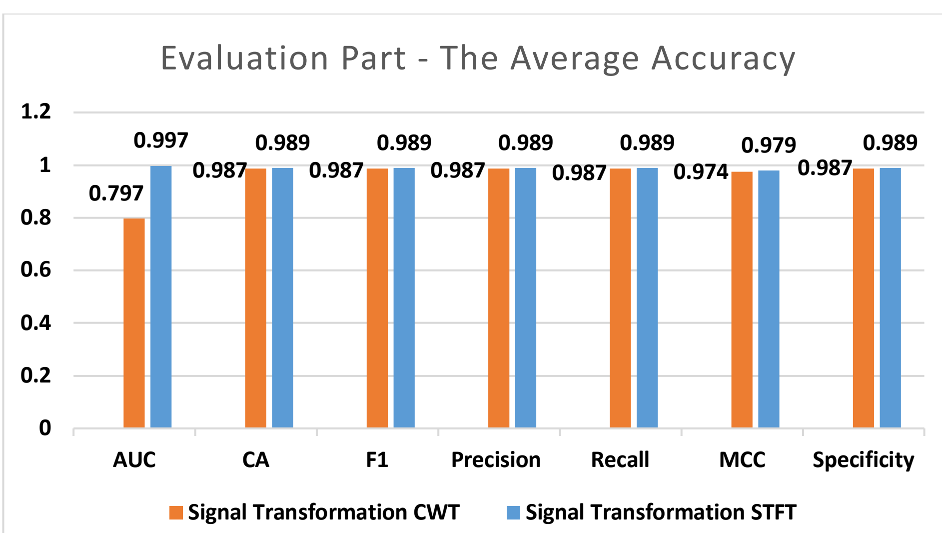

Fig. 5. The Average Accuracy at Evaluation Part using CWT and STFT

The training result of the proposed hybrid model showed that the average accuracy achieved by STFT is higher than CWT. This means the STFT transformation is more precise for classification to the current dataset (nine subjects), resulting in more effective hybrid CNN model training. Furthermore, the evaluation result of the proposed hybrid model, showed that the average accuracy achieved by STFT, is higher than CWT in the evaluation metrics. This indicates that STFT-based features conduct a more accurate and reliable model on unseen data. It indicates that the STFT is a better choice for feature extraction in this scenario, as it improves generalization and robustness for the hybrid CNN model with logistic regression.

5. FUTURE WORK

The future work for this study consists of several directions on improvement and further research. Explore the possibility of using the developed hybrid deep learning model with different types of MI signals other than the one used to train the model. It could be using other methods of signal processing or use a number of techniques together in order to increase the model's resilience. Further, incorporating real-time feedbacks could enhance the interaction of the system to enhance responsiveness of the system to the disabled users.

On the other hand, future work can be the improvement and the generalization ability of the model, for instance, incorporating adversarial robustness into the model. Because of the improvement of the advanced adversarial attacks like FGSM or PGD, it is significant to examine the susceptibility of the BCI systems to those threats [88][89]. The threats brought by adversarial attacks are especially high in BCIs since manipulated inputs could cause wrong commands or actions. In future research, more emphasis may be placed on adversarial training, in which clean and adversarial examples are used in order to improve the robustness of the created models. Techniques such as input preprocessing, distillation, as well as model ensembling are possible to be adapted based on the methodology mentioned earlier for combating noisy and non-stationary MI EEG signals effectively and strongly against adversarial attacks [88][90]. Moreover, further investigation of data adaptive forms of signal processing that would depend on characteristics of the EEG signal might facilitate the enhancement of both the stability and reliability of the system [37][91]. It also involves using feedback loops that change model parameters or signal processing algorithms as soon as categories of adversarial behavior are noted. Apart from enhancing the reliability of BCI systems, these enhancements can go to other frontiers such as, cognitive rehabilitation, smart home automation and control, and security where secure BCI systems are needed. For instance, enhancing security for BCI systems specifically designed for households could be enhanced by these strategies as a way of protecting its users against incidences of attacks.

Additionally, directions must include reducing latency while increasing the efficiency of real-time adaptation to increase the actual usefulness of systems, adding real-time adversarial recognition and counteraction abilities to guarantee uninterrupted, faultless operation. The integration of knowledge from neuroscience, computer science, cybersecurity, and robotics in particular could help to create higher complexity models which would be able to process more signals from the brain with a greater accuracy and at the same time maintain resistance to adversarial manipulation. Such advancements will be decisive for the effective implementation of BCIs and other assistive technologies in sensitive areas to make it effective, secure from an external attack, and improve the use of assistive technologies in various fields to the benefit of the entire field of assistive technologies.

6. CONCLUSION

This work describes a new method of actuating the motion of a robotic arm with the help of a deep learning model based on Inception V3 and containing a conventional classifier. Based on signal analysis, it became evident that the application of the STFT of the MI signals results in better classification of the signals which consequently results in better control of the hand movements of the robot. This advancement is important for improvement of the preserving and improving the quality of life of disabled people. Not only does the proposed model effectively interpret the user inputs it also owns good potentiality to be adopted in daily schedule due to its simple and smooth working nature. Furthermore, these finding emphasize the need to select proper methods of signal analysis in case of very high non-stationary data of MI EEG, which is crucial for accurate and reliable results. Although the existing model revealed significant applicability there are issues left such as accommodation for differences in signal pattern in diffident individuals and latency issues for momentary control. It is therefore conceivable that addressing some of these challenges could serve to improve both user experience of the system as well as the system's functionality. The presented results of this study are significant to the body of knowledge in assistive technology where this study provided new insights on the possibility of utilizing deep learning to operate robotic devices. The future likely holds further progress in pushing the applicative envelope more than just applying speech assistance tools for improving impaired cognition to augment the common tools for providing cognitive rehabilitation; exploiting speech assistance to create intelligent home environments to have a noteworthy positive impact on many users' lives. This work suggests further works and research in this direction to come up with more enhanced and variable assistive technologies in future.

Conflicts Of Interest

The authors declare no conflicts of interest.

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